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A Fast Harmony Search Algorithm for Unimodal Optimization with Application to Power System Economic Dispatch

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1. Introduction

Evolutionary algorithms are general-purpose stochastic search methods simulating natural selection and biological evolution. They differ from other optimization methods in the fact maintaining a population of potential solutions to a problem, and not just one solution. Generally, these algorithms work as follows: a population of individuals is randomly initialized where each individual represents a potential solution to the problem. The quality of each solution is evaluated using a fitness function. A selection process is applied during each iteration in order to form a new solution population. This procedure is repeated until convergence is reached. The best solution found is expected to be a near-optimum solution.

HSA that was recently proposed by Greem and al (Greem et al, 2001) is an evolutionary algorithm imitating the improvisation process of musicians. This process is constituted of three steps, in the original HSA, with a fourth step added in the improved version (Geem, 2006). In order to improve the fine–tuning characteristic of HSA, Mahdavi and al developed an Improved Harmony Search Algorithm (IHSA) that differs from original HSA in the fact that some parameters (pitch adjusting rate "PAR" and bandwidth "bw") are adjusted during the improvisation process (Mahdavi et al, 2007). Omran and al proposed another version of HSA named Global-best Harmony Search Algorithm (GHSA), which borrows concepts from swarm intelligence to enhance the performance of HSA (Omran & Mahdavi, 2008). GHSA is an IHSA version with the pitch-adjustment modified such that the new harmony can mimic the best harmony in the Harmony Memory (HM).

In this paper, we propose a Fast version of HSA for the optimization of unimodal quadratic functions. The results (optimum solution and number of improvisations) of HSA, IHSA, GHSA and FHSA are compared for some convex functions (De Jong's function and rotated hyper-ellipsoid function) then for Economic Dispatch (ED).

The ED problem is one of the important optimization problems in power system. Generally, the cost function of each generator is approximately represented by a quadratic function (Wallach & Even, 1986) with a need of a real time response from the optimization system (Rahli & Pirotte, 1999). Therefore, we investigate the effectiveness and the accuracy of different versions of HSA and our proposed version.

2. Economic dispatch

Economic dispatch is the important component of power system optimization. It is defined as the minimization of the combination of the power generation, which minimizes the total cost while satisfying the power balance relation (Benasla et al, 2008)[a]. The problem of economic dispatch can be formulated as minimization of the cost function subjected to the equality and inequality constraints (Benasla et al, 2008)[b].

In power stations, every generator has its input/output curve. It has the fuel input as a function of the power output. But if the ordinates are multiplied by the cost of $/Btu, the result gives the fuel cost per hour as a function of power output (Wallach & Even, 1986).

In the practical cases, the fuel cost of generator i may be represented as a quadratic function of real power generation:

$$F_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{1}$$

The objective function for the entire power system can then be written as the sum of the quadratic cost model at each generator.

This objective function will minimize the total system costs.

$$\text{Min}\left\{ F = \sum_{i=1}^{ng} F_i(P_{Gi}) \right\} \tag{2}$$

Where F is the total fuel cost of the system, P_{Gi} real power output, ng is the number of generators including the slack bus a_i, b_i and c_i are the cost coefficients of the i-th unit.

Constraints

1. Power balance constraints. The total power generation must cover the total demand P_{ch} and the real power loss in the transmission lines P_L. Hence

$$\sum_{i=1}^{ng} P_{Gi} - P_L - P_{ch} = 0 \tag{3}$$

2. Generation capacity constraints. For stable operation, the generator outputs are restricted by lower and upper limits as follows:

$$P_{Gimin} \le P_{Gi} \le P_{Gimax} \tag{4}$$

3. The Harmony Search Algorithms

The HSA is inspired from the musical process of searching for a perfect state of harmony (Greem et al, 2001). All Harmony Search versions consider the optimization problem defined as:

$$\text{Max or Min } f(x^j) \quad j = 1,\dots,p$$

Subject to: $x^j_{min} \le x^j \le x^j_{max}$

The optimization process is directed by four parameters (belmadani et al, 2009):

1. Harmony Memory Size (HMS) is the number of solution vectors stored in HM.
2. Harmony Memory Considering Rate (HMCR) is the probability of choosing one value from HM and (1-HMCR) is the probability of randomly choosing one new feasible value.
3. Pitch Adjusting Rate (PAR) is the probability of choosing a neighboring value of that chosen from HM.
4. Distance bandwidth (bw) defines the neighborhood of a value as [$x^j \pm bw \times U(0,1)$]. U(0,1) is a uniform distribution between 0 and 1.

Another intuitively important parameter is the Number of Iterations (NI) which is the stop criterion of the three previous versions of HSA.

HSA works as follows:

Step 1. Initialize the problem and HSA parameters.
Step 2. Initialize HM by randomly generated (improvised) harmonies.
Step 3. Improvise a new harmony as follows:

```
for j=1 to p do
if  U(0,1) > HMCR  then        x^j = x^j_min + (x^j_max − x^j_min) × U(0,1)
else (*Memory consideration*)
 begin
  x^j = x_i^j where i ≈ U(1,HMS)
 if U(0,1) ≤ PAR then (*pitch adjustment*)
   begin
 x^j = x^j ± bw × U(0,1)
   endif
 endif
done
```

Step 4. If the New Harmony (NH) is better than the Worst Harmony (WH) in HM then replace WH by NH.
Step 5. Reiter Steps 3 and 4 until satisfaction of the stop criterion.

The IHSA dynamically updates PAR and bw in improvisation step (Step 3). These two parameters change dynamically with generation number as follows:

$$PAR = PAR_{min} + \frac{PAR_{max} - PAR_{min}}{NI} \times gn \quad \text{and} \quad bw = bw_{max} \times e^{\left(\frac{Ln\left(\frac{bw_{min}}{bw_{max}}\right)}{NI}\right) \times gn}$$

where
PAR_{min} : minimum pitch adjusting rate
PAR_{max} : maximum pitch adjusting rate
NI : number of iterations
gn : generation number
bw_{min} : minimum bandwidth and bw_{max} : maximum bandwidth

The GHSA modifies the pitch adjustment step of the IHSA as follows:

if $U(0,1) \le PAR$ then (*pitch adjustment*)
begin
$x^j = x^k_{best}$
endif

where best is the index of the best harmony in the HM and $k \approx U(1,p)$. This pitch adjustment is inspired by the concept of swarm intelligence in Particle Swarm Optimization. The position of a particle is influenced by the best position visited by itself and the best particle in the swarm.

3.1 Proposed method

The new version of HSA, proposed in this paper, is inspired by the concept of reactive search (Battiti et al, 2007) where parameter tuning, which is usually performed offline by the researcher, becomes an integral part of the search algorithm, ensuring flexibility without human intervention. The "learning" component is implemented as a reactive feedback scheme that uses the past history of the search to increase its efficiency and efficacy.
The new approach, called Fast Harmony Search Algorithm (FHSA), introduces a prohibition step between step 4 and step 5 as shown in figure 1. It consists in defining a permanent prohibition of the search space (bounds adjustment) to prevent the system from going back on its track.

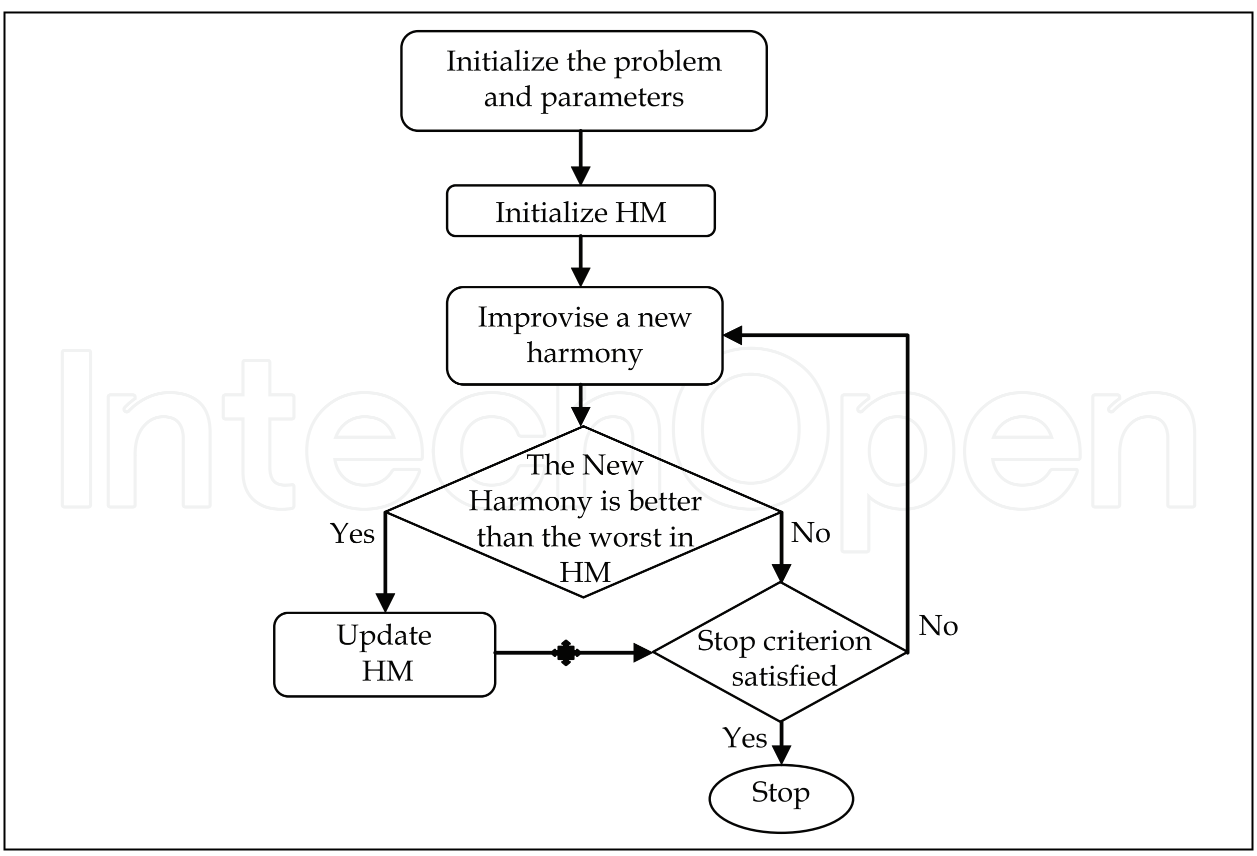

Fig. 1. Optimization procedure of HSA (✥ FHSA bounds adjustment point.)

This prohibition excludes any considered "none interesting" region from the search by adjusting the upper and/or lower bound of each decision variable and is performed as follows:

for j=1 to p do
if $f(x^j + \delta) < f(x^j)$ then $x^j_{min} = x^j + \delta$
else
if $f(x^j - \delta) < f(x^j)$ then $x^j_{max} = x^j - \delta$
else
$x^j_{max} = x^j$ and $x^j_{min} = x^j$
endif
done

The stop criterion becomes:

if $(x^j_{max} - x^j_{min}) \le \varepsilon \quad j = 1,\ldots,p$ then STOP endif

where δ is a real number "small enough" and ε is the precision term.
Since the search space of each variable is reduced then bw must be adjusted in accordance with this reduction. So it becomes:

$$bw = \frac{\left(x^j_{max} - x^j_{min}\right)}{c}$$

Where c is an integer, generally taken as a multiple of 10.

3.2 Examples

In order to demonstrate the performance of the FHSA, we compare it's results with those of HSA, IHSA and GHSA on these two convex and unimodal functions:
De Jong's function: It is also known as sphere model. It is continuous, convex, unimodal and defined as:

$$f_1(x) = \sum_{j=1}^{p} \left(x^j\right)^2$$

$$\text{where } x^j_{min} \le x^j \le x^j_{max} \qquad j = 1,\ldots,p$$

Rotated hyper-ellipsoid function: It is continuous, convex, unimodal and defined as:

$$f_2(x) = \sum_{i=1}^{p} \Big(\sum_{j=1}^{i} \left(x^j\right) \Big)^2$$

$$\text{where } x^j_{min} \le x^j \le x^j_{max} \qquad j = 1,\ldots,p$$

These two functions have the same optimum: $\begin{cases} f^*(x^j) = 0, \\ x^j = 0 \quad \text{for} \quad j = 1,\ldots,p \end{cases}$

HSA, IHSA and GHSA were allowed to run for 500,000 iterations with a value of HMS=10 and HMCR=0.95. The other parameters were adjusted to obtain the best possible solution. For FHSA, the new parameters δ and ε were set to:

$$\delta = \frac{(x^j_{max} - x^j_{min})}{50} \quad \text{and} \quad \varepsilon = 10^{-14}$$

For HSA: $bw = \frac{(x^j_{max} - x^j_{min})}{10^6}$

For IHSA: $bw_{min} = \frac{(x^j_{max} - x^j_{min})}{10^9}, \quad bw_{max} = \frac{(x^j_{max} - x^j_{min})}{10^4}$

For both IHSA and GHSA: PAR_{min}=0.01 and PAR_{max}=0.99

We first take a basic case where the space dimension (number of variables P) is set to 30 and the upper bound of each variable is set to 10^3 (figure 2 and figure 6). Then we explore the effect of increasing the space dimension (figure 3 and figure 7). Figure 4 and figure 8 represent the effect of increasing the upper bounds (x^j_{max}). Finally the effect of increasing space dimension and upper bounds is shown in figure 5 and figure 9. The lower bound is set for all cases to x^j_{min}=0. The results of the optimal solution and computing time are grouped in Table 1 and Table 2. For FHSA a column is added to represent the Number of Function Evaluations (NFE) needed by the algorithm to satisfy the stop criterion. The computational results are obtained using an Intel Pentium Dual CPU @ 1.80 GHz and TURBO PASCAL compiler.

		P=30, x^j_{max} =10^3	P=100, x^j_{max} =10^3	P=30, x^j_{max} =10^6	P=100, x^j_{max} =10^6
HSA	optimum	5.53E-7	5244.57	0.55	5.24E9
	time (s)	12.610	40.484	12.672	40.594
IHSA	optimum	1,01E-11	7904.41	1.01E-5	7.90E9
	time (s)	13.469	43.531	13.453	43.422
GHSA	optimum	83.63E-3	14.26	80977.46	1.43E7
	time (s)	13.016	42.297	12.796	42.266
FHSA	optimum	1.36E-28	1.10E-27	3.03E-28	1.24E-27
	time (s)	0.110	0.656	0.125	0.750
	NFE	1237	1204	1315	1437

Table 1. Optimal solution and time of execution for De Jong's function

		P=30, x^j_{max} =10^3	P=100, x^j_{max}=10^3	P=30, x^j_{max} =10^6	P=100, x^j_{max} =10^6
HSA	optimum	0.48	5.49E9	48.40E4	5.49E15
	time (s)	24.469	230.547	29.406	230.546
IHSA	optimum	10.48	7.61E9	1.05E7	7.61E15
	time (s)	31.359	244.329	31.343	244.360
GHSA	optimum	264.73	7.67E7	2.65E8	7.67E13
	time (s)	29.578	232.235	29.656	233.641
FHSA	optimum	1.48E-25	1.31E-20	1.18E-25	8.31E-21
	time (s)	6.078	93.719	7.110	111.937
	NFE	41,202	23,133	47,896	29,388

Table 2. Optimal solution and time of execution for Rotated hyper-ellipsoid function

These results show clearly that FHSA is more stable for higher dimensions and higher search spaces than the three previous versions. Moreover, it performed better than its predecessors in a lower time. The rate of convergence of HSA, IHSA and GHSA is slow, requiring a relatively greater number of function evaluations to obtain the optimal solution than the FHSA. The time for the FHSA decreases slightly because the number of function evaluations is reduced by the reduction of the search space. Moreover, defining a permanent prohibition of the search space contributes to the minimization of the size of HM, so there is no need of a large HMS.

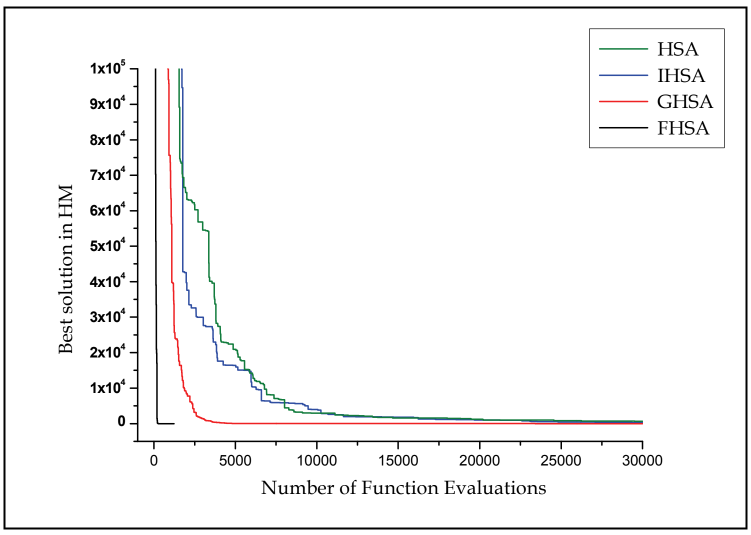

Fig. 2. Optimization of $f_1(x)$ with P=30 and $x^j_{max}=10^3$

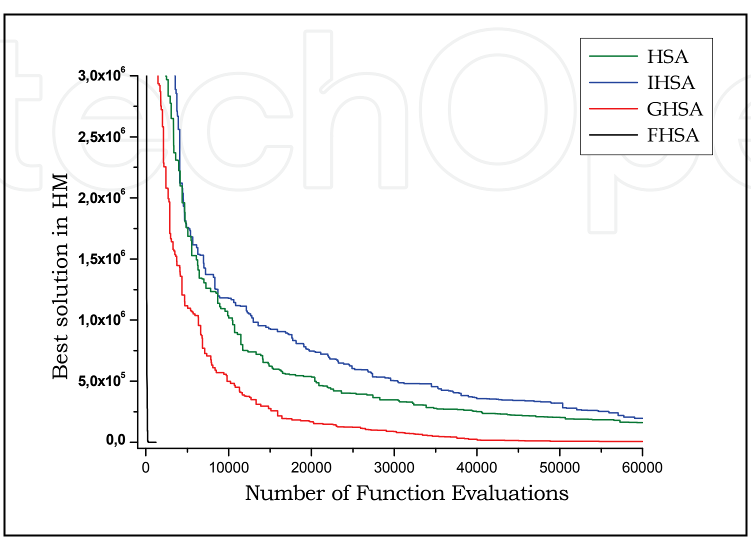

Fig. 3. Optimization of $f_1(x)$ with P=100 and $x^j_{max}=10^3$

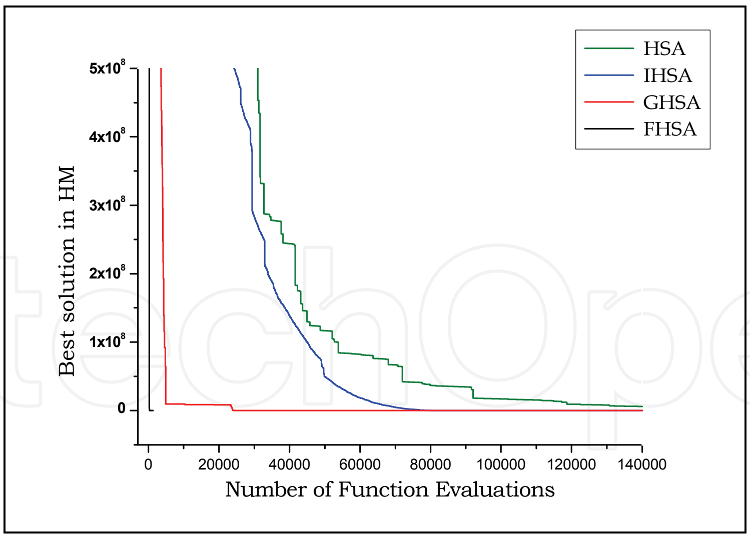

Fig. 4. Optimization of $f_1(x)$ with P=30 and xj_{max} =10^6

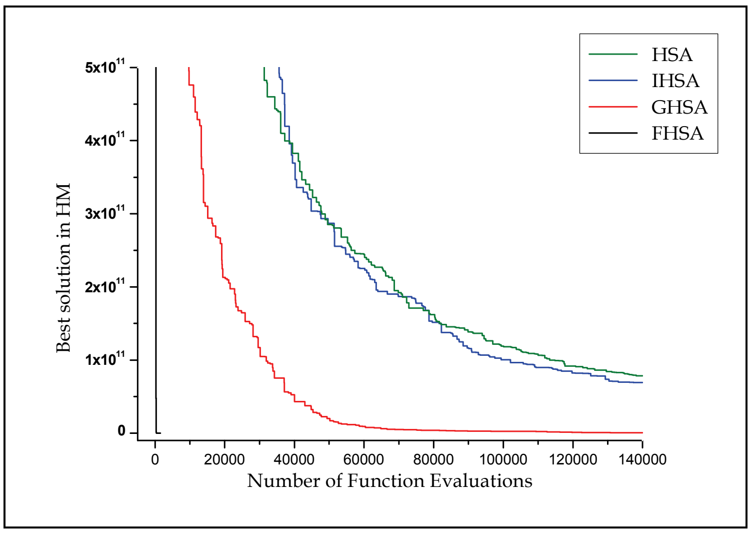

Fig. 5. Optimization of $f_1(x)$ with P=100 and xj_{max} =10^6

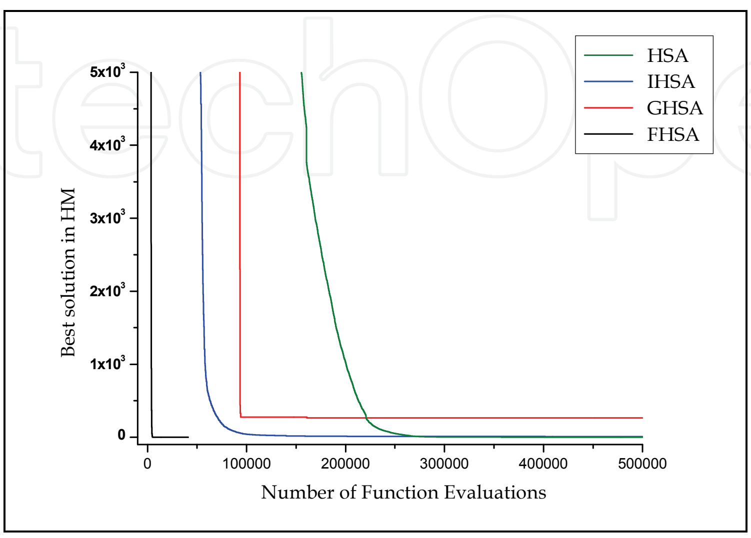

Fig. 6. Optimization of $f_2(x)$ with P=30 and xj_{max} =10^3

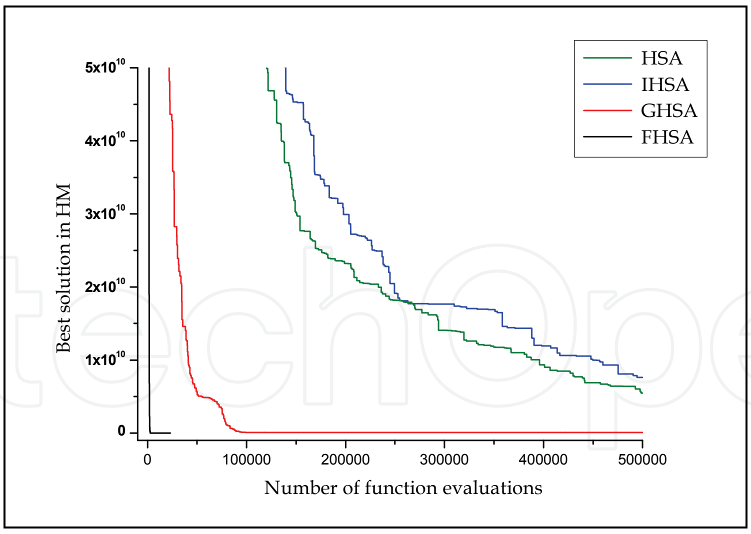

Fig. 7. Optimization of $f_2(x)$ with P=100 and xj_{max} =10^3

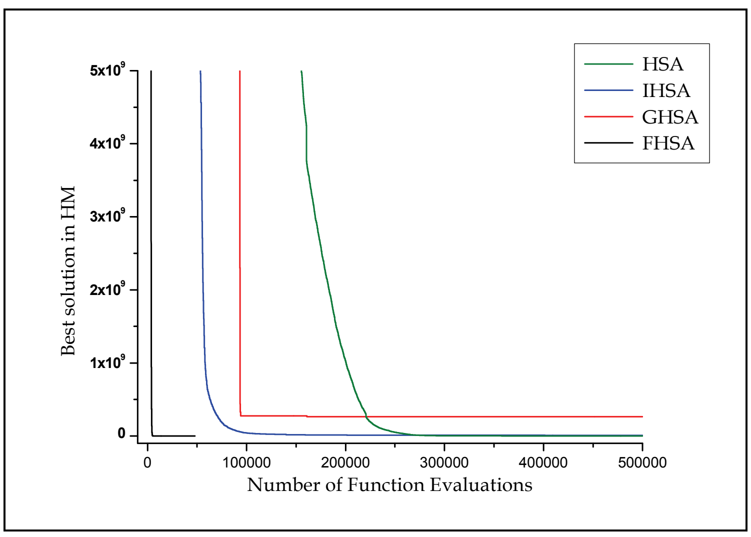

Fig. 8. Optimization of $f_2(x)$ with P=30 and xj_{max} =10^6

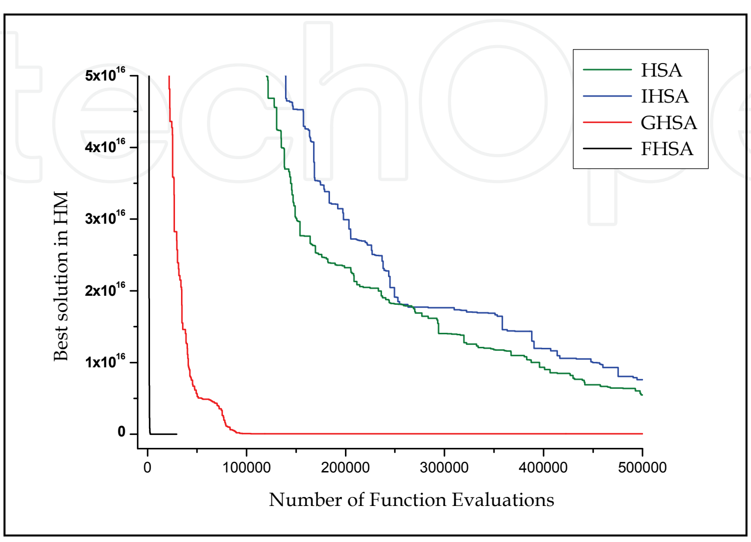

Fig. 9. Optimization of $f_2(x)$ with P=100 and xj_{max} =10^6

We have shown that the reduction of the search space contributes extensively to the effectiveness of the optimization process by Harmony Search. While knowing that Harmony Search Algorithm was originally inspired from the improvisation process of a group of musicians, the so called "reduction of the search space" might be considered as a manifestation of the experience of a performer.
Indeed, an experienced player can perceive during a concert that a pitch higher and/or lower than the actual may lead not into good harmony (music). He will, then, decide to avoid playing those pitches. This reality is implemented in FHSA as the reduction of the search space which affects directly the Harmony Memory and its Considering Rate HMCR.
The Harmony Memory Considering Rate is a major and dominant parameter in the optimization process by Harmony Search. Its role is to insure that good harmonies (good values of decision variables) are considered as elements of the new solution vectors. If this rate is too low, only few elite harmonies are selected and it may converge too slowly. If this rate is extremely high (near 1), the pitches in the harmony memory are mostly used, and other ones are not explored well, leading not into good solutions. Therefore, typically, HMCR is taken in the interval [0.7, 0.95] (Yang, 2009).
The central component of the optimization process by Harmony Search is the pitch adjustment which has parameters such as distance bandwidth bw and pitch adjusting rate PAR. As the pitch adjustment in music means changing the frequency, it means generating a slightly different value in the HS algorithm (Geem et al., 2001).
Pitch adjustment is similar to the mutation operator in genetic algorithms. We can assign a pitch adjusting rate to control the degree of the adjustment.
A low pitch adjusting rate with a narrow bandwidth can slow down the convergence of HS because of the limitation in the exploration of only a small subspace of the whole search space. On the other hand, a very high pitch-adjusting rate with a wide bandwidth may cause the solution to scatter around some potential optima as in a random search. Thus, in most applications, PAR is usually taken in the interval [0.1 , 0.5] (Yang, 2009).
In this section we investigate the effect of HMCR on the optimization process of HSA, IHSA, GHSA and FHSA. As an example, we use the De Jong's function with the four cases of increasing the search space and/or the space dimension. The four cases are:

CASE 1. P=30 and $x^j_{max}=10^3$

CASE 2. P=100 and $x^j_{max}=10^3$

CASE 3. P=30 and $x^j_{max}=10^6$

CASE 4. P=100 and $x^j_{max}=10^6$

For each case we apply the four versions of Harmony Search Algorithm with different values of HMCR. The values chosen are:

HMCR =0.95, HMCR=0.9, HMCR=0.8 and HMCR=0.7.

We do not investigate the PAR effect because it is dynamically adjusted in IHSA and GHSA. For HSA and FHSA, we maintain this parameter set to the mean value PAR=0.5.
The results are shown in the tables 3 to 6 and detailed in figure 10 to figure 25. The stop criterion of HSA, IHSA and GHSA is a maximum number of iterations NI=500,000 and the size of HM is set to HMS=10.

The other parameters are taken as follow:

HSA: PAR=0.5, $bw = \frac{(x^j_{max} - x^j_{min})}{10^6}$

IHSA: $PAR_{min} = 0.01$, $PAR_{max} = 0.99$, $bw_{min} = \frac{(x^j_{max} - x^j_{min})}{10^9}$, $bw_{max} = \frac{(x^j_{max} - x^j_{min})}{10^4}$

GHSA: $PAR_{min} = 0.01$, $PAR_{max} = 0.99$

FHSA : HMS=2, PAR =0.5, $\delta = \frac{(x^j_{max} - x^j_{min})}{50}$, $\varepsilon = 10^{-14}$

The results show a greater stability of FHSA to the diminution of HMCR.
The curves of figures 10 to 21 contain constant areas which frequency is conversely proportional to the value of HMCR. These constancies mean that the optimization process is slowed down by the diminution of HMCR. Consequently, we can conclude that the three previous version of the Harmony search algorithm are essentially based on the pitch adjustment component.
Like its predecessors, FHSA is affected by the diminution of HMCR (figures 22 to 25) but in a different way. The fact of randomly generating new solutions contributes strongly to the reduction of the search space giving rise to the acceleration of the optimization process. Taking a value of HMCR 5% lower reduce to about 50% the Number of function Evaluations needed by the algorithm to stop. However, greater values of HMCR offer a better precision of the optimal solution.

HSA (PAR=0.5)	P=30, $x^j_{max} = 10^3$	P=100, $x^j_{max} = 10^3$	P=30, $x^j_{max} = 10^6$	P=100, $x^j_{max} = 10^6$
HMCR=0.95	1.60E-6	6064.92	1.60	6.07E9
HMCR=0.9	3.66	596 187.99	3.66E6	5.96E11
HMCR=0.8	1 863.71	3.05E6	1.86E9	3.05E12
HMCR=0.7	83 644.48	6.73E6	8.36E10	6.73E12

Table 3. Results of optimization by HSA with different values of HMCR

IHSA	P=30, $x^j_{max} = 10^3$	P=100, $x^j_{max} = 10^3$	P=30, $x^j_{max} = 10^6$	P=100, $x^j_{max} = 10^6$
HMCR=0.95	1.026E-11	8 106.56	1.03E-5	8.11E9
HMCR=0.9	7.83	720 922.93	7.83E6	7.21E11
HMCR=0.8	2 123.89	3.66E6	2.12E9	3.66E12
HMCR=0.7	132 335.77	6.64E6	1.32E11	6.64E12

Table 4. Results of optimization by IHSA with different values of HMCR

GHSA	P=30, x^j_{max} =10^3	P=100, x^j_{max} =10^3	P=30, x^j_{max} =10^6	P=100, x^j_{max} =10^6
HMCR=0.95	2.76E-5	61.63	5609.54	6.16E7
HMCR=0.9	2.76E-5	107 227.36	27.57	1.07E11
HMCR=0.8	1.33	2.35E6	1.39E6	2.35E12
HMCR=0.7	20 075.84	4.78E6	2.01E10	4.78E12

Table 5. Results of optimization by GHSA with different values of HMCR

FHSA (PAR=0.5)		P=30, x^j_{max} =10^3	P=100, x^j_{max} =10^3	P=30, x^j_{max} =10^6	P=100, x^j_{max} =10^6
HMCR=0.95	optimum	3.20E-28	8.95E-28	3.11E-28	7.90E-28
	NFE	1095	1489	1209	1671
HMCR=0.9	optimum	3.66E-28	9.68E-28	1.75E-28	1.08E-27
	NFE	528	623	601	686
HMCR=0.8	optimum	3.18E-28	1.06E-27	2.21E-28	1.18E-27
	NFE	277	316	318	342
HMCR=0.7	optimum	2.96E-28	1.10E-27	3.10E-28	1.14E-27
	NFE	199	204	232	235

Table 6. Results of optimization by FHSA with different values of HMCR

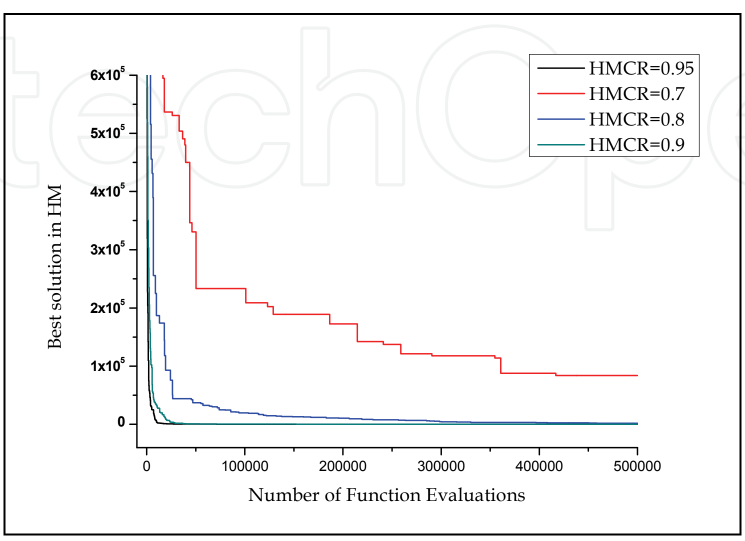

Fig. 10. Detailed results of HSA –CASE 1-

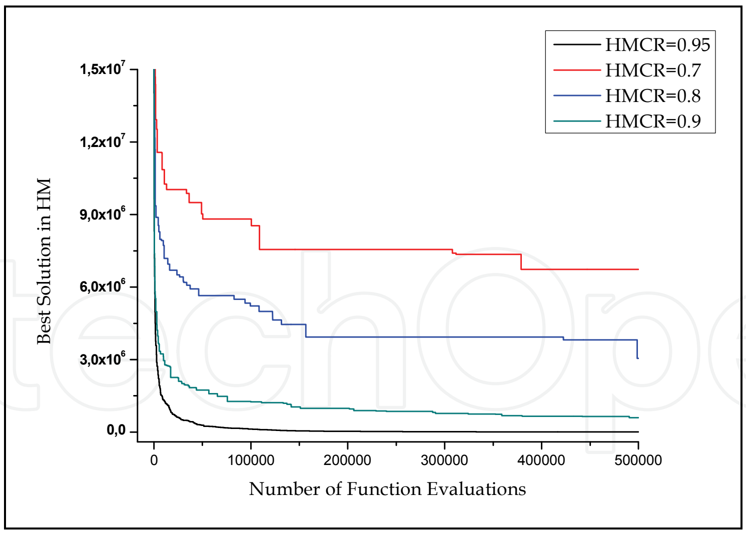

Fig. 11. Detailed results of HSA –CASE 2-

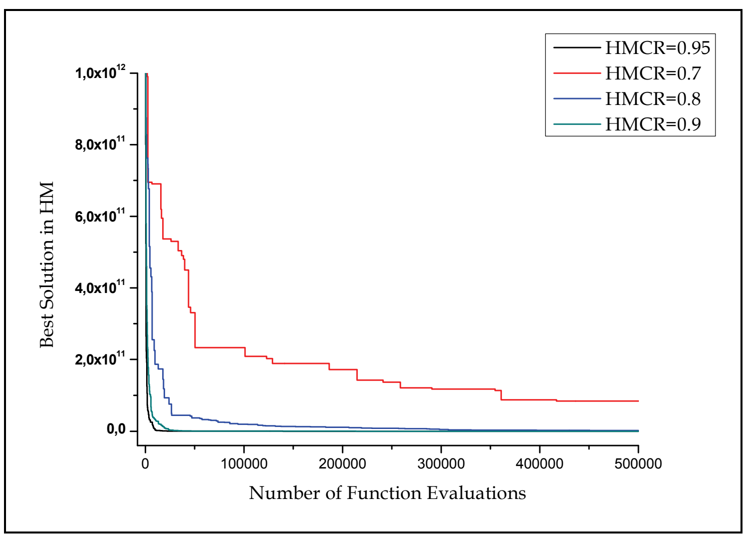

Fig. 12. Detailed results of HSA –CASE 3-

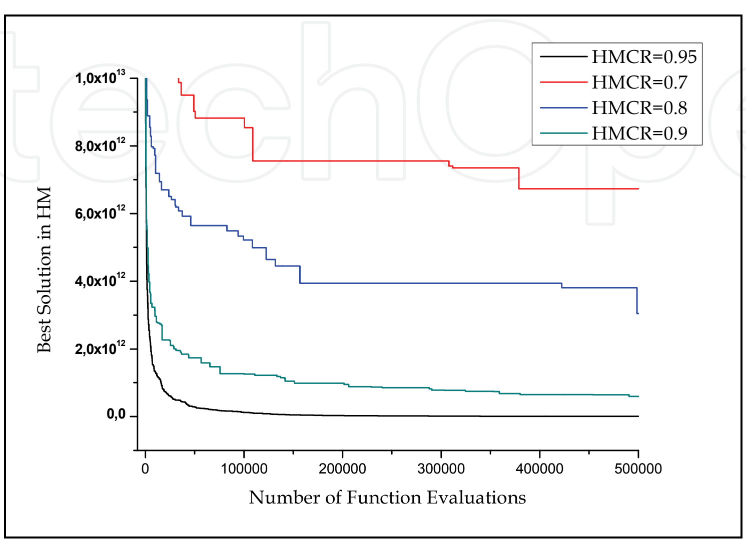

Fig. 13. Detailed results of HSA –CASE 4-

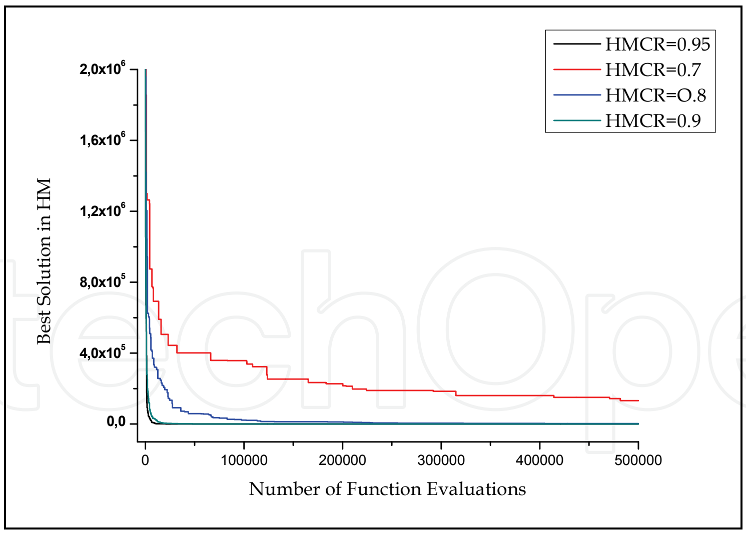

Fig. 14. Detailed results of IHSA –CASE 1-

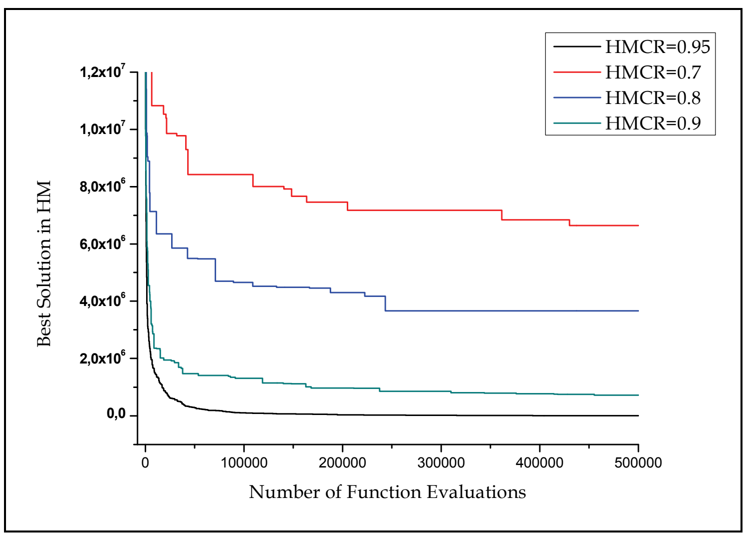

Fig. 15. Detailed results of IHSA –CASE 2-

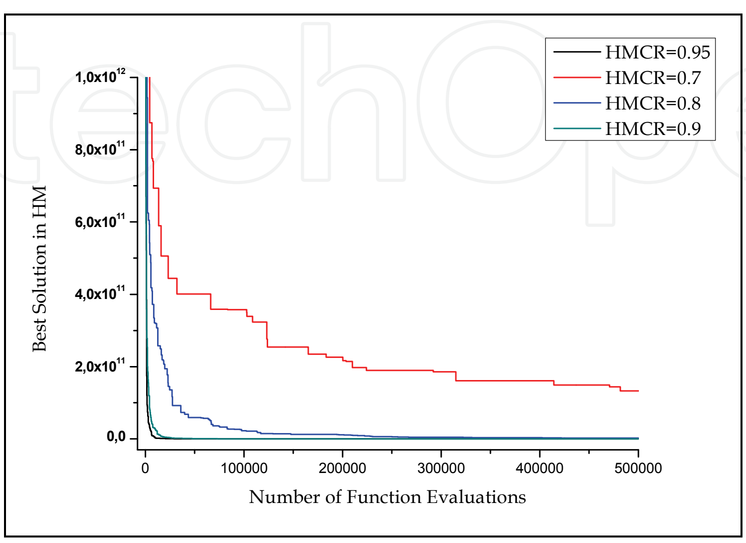

Fig. 16. Detailed results of IHSA –CASE 3-

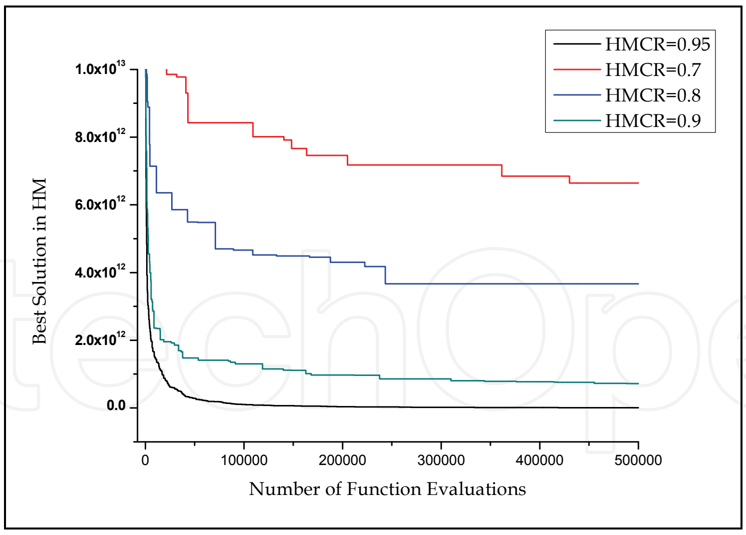

Fig. 17. Detailed results of IHSA –CASE 4-

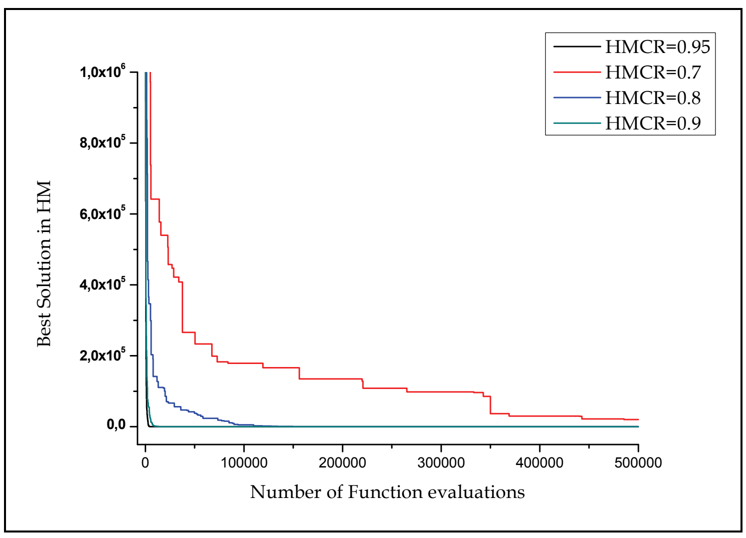

Fig. 18. Detailed results of GHSA –CASE 1-

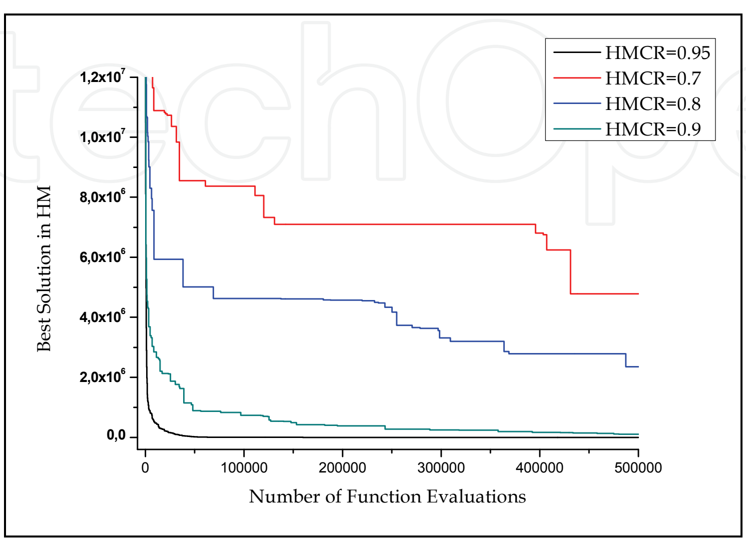

Fig. 19. Detailed results of GHSA –CASE 2-

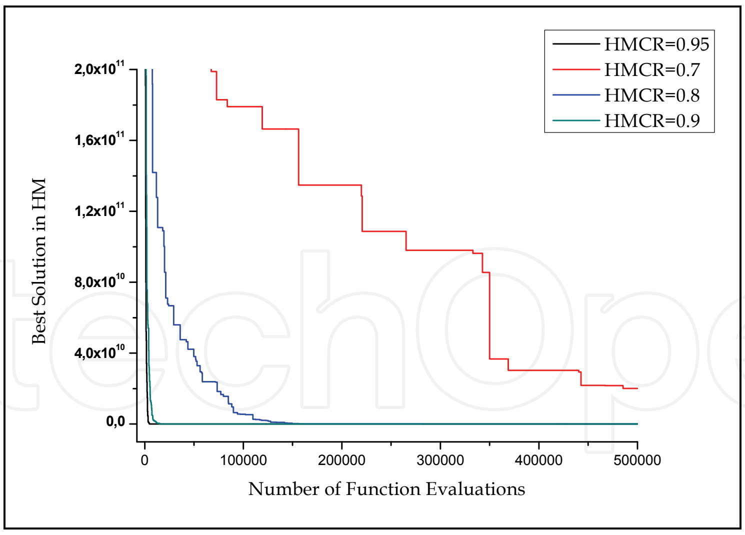

Fig. 20. Detailed results of GHSA –CASE 3-

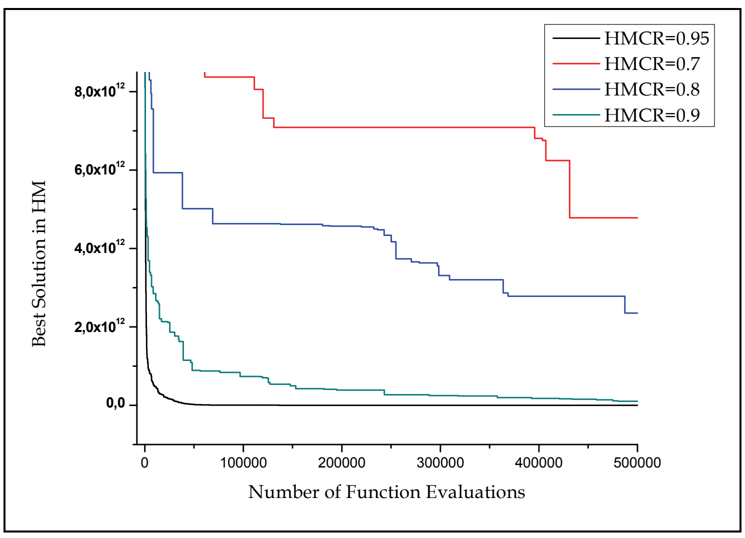

Fig. 21. Detailed results of GHSA –CASE 4-

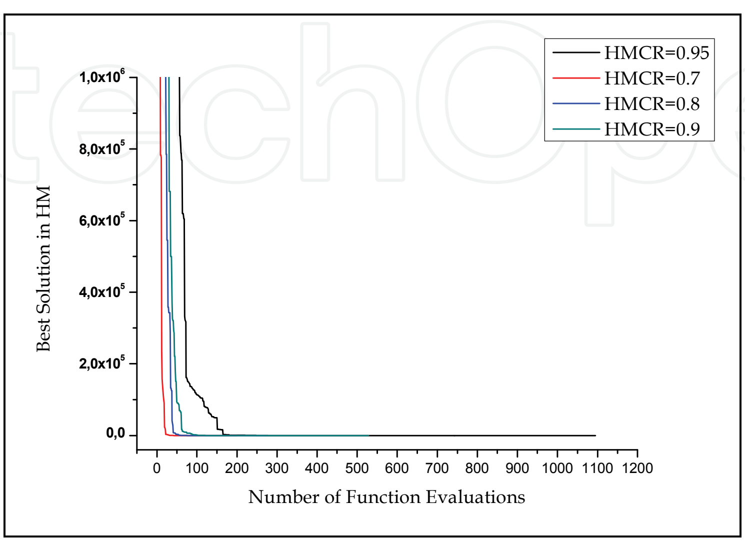

Fig. 22. Detailed results of FHSA –CASE 1-

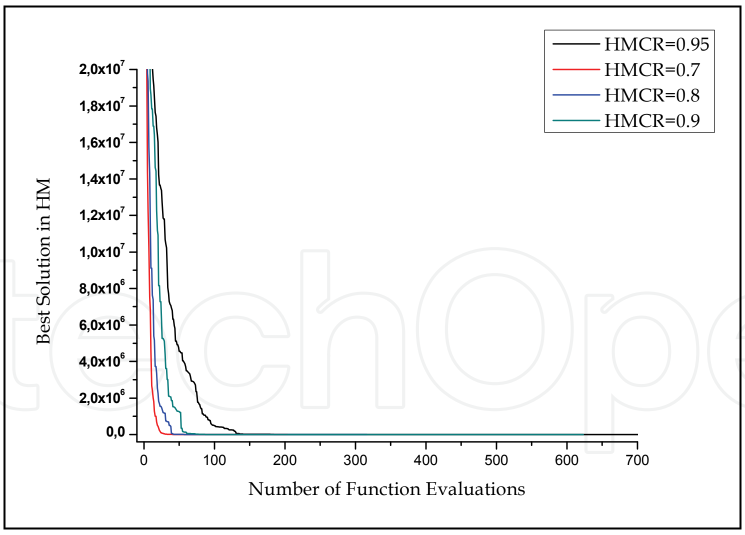

Fig. 23. Detailed results of FHSA –CASE 2-

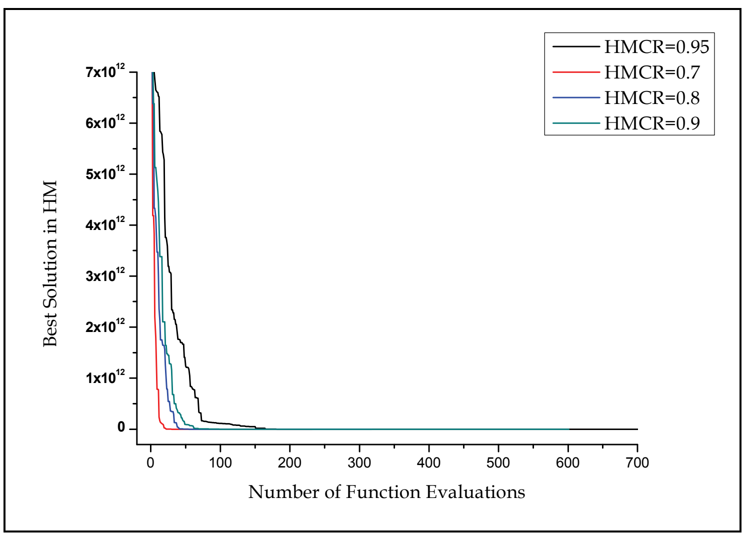

Fig. 24. Detailed results of FHSA –CASE 3-

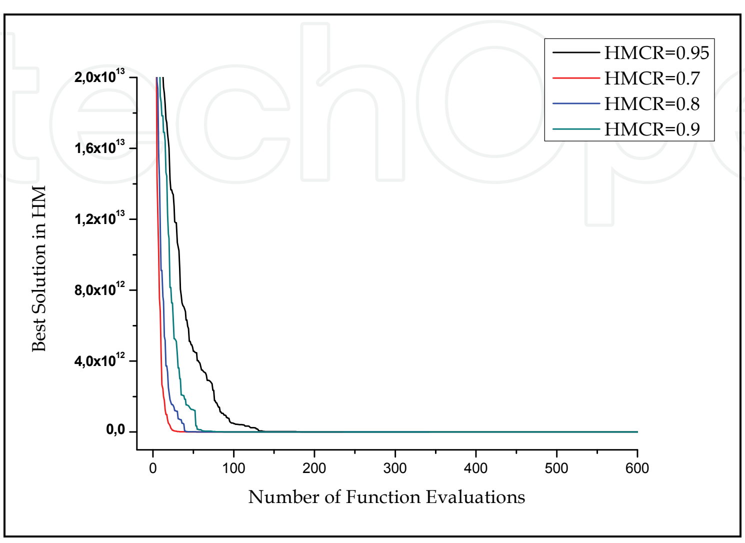

Fig. 25. Detailed results of FHSA –CASE 4-

4. Application

The proposed algorithm is applied to IEEE-118. The system has 54 thermal units. Generators characteristics, that is, cost coefficients and generation limits, are taken from Matpower web site (Zimmerman et al., accessed on 2008) and its detailed data are given in Wallach's book (Wallach & Even, 1986). The generators characteristics, power generation limits and generator cost parameters are given in table 7 and table 8. The computational results are obtained using an Intel Pentium Dual CPU @ 1.80 GHz and TURBO PASCAL compiler.

Gen	1	4	6	8	10	12	15	18	19	24	25	26	27	31	32	34	36	40
Type	#1	#1	#1	#1	#2	#3	#1	#1	#1	#1	#4	#5	#1	#6	#1	#1	#1	#1
Gen	42	46	49	54	55	56	59	61	62	65	66	69	70	72	73	74	76	77
Type	#1	#7	#8	#9	#1	#1	#10	#11	#1	#12	#13	#14	#1	#1	#1	#1	#1	#1
Gen	80	85	87	89	90	91	92	99	100	103	104	105	107	110	111	112	113	116
Type	#15	#1	#16	#17	#1	#1	#1	#1	#18	#19	#1	#1	#1	#1	#20	#1	#1	#1

Table 7. Characteristic of 54 Generators of network 118 – bus

Type	$P_{Gi\min}$ (MW)	$P_{Gi\max}$ (MW)	a_i (\$/MW².hr)	b_i (\$/MW.hr)	c_i (\$/hr)
#1	10	100	0.01	40	0.0
#2	55	550	0.0222222	20	0.0
#3	18.5	185	0.117647	20	0.0
#4	32	320	0.0454545	20	0.0
#5	41.4	414	0.0318471	20	0.0
#6	10.7	107	1.42857	20	0.0
#7	11.9	119	0.526316	20	0.0
#8	30.4	304	0.0490196	20	0.0
#9	14.8	148	0.208333	20	0.0
#10	26	255	0.0645161	20	0.0
#11	26	260	0.0625	20	0.0
#12	49.1	491	0.0255754	20	0.0
#13	49.1	492	0.0255102	20	0.0
#14	80.5	805.2	0.0193648	20	0.0
#15	57.7	577	0.0209644	20	0.0
#16	10.4	104	2.5	20	0.0
#17	70.7	707	0.01644745	20	0.0
#18	35.2	352	0.0396825	20	0.0
#19	14	140	0.25	20	0.0
#20	13.6	136	0.277778	20	0.0

Table 8. Power generation limits and generator cost parameters of networks 118-bus system

In order to demonstrate the performance of the proposed Algorithm, a comparison emerges between FHSA applied to the ED and other optimization methods, as it is shown in table 9 and figure 26. The parameters of the algorithms are taken as follow

FHSA: $PAR = 0.7, HMCR = 0.95$, $\varepsilon = 10^{-15}$ and $\delta = \dfrac{P_{Gimax} - P_{Gimin}}{5.10^7}$

HSA: $PAR = 0.7$ and $bw = 3$.

IHSA: $PAR_{min} = 0.01, PAR_{max} = 0.99$, $bw_{min} = 10^{-3}$ and $bw_{max} = 10^{+3}$

GHSA: $PAR_{min} = 0.001, PAR_{max} = 0.999$

HSA, IHSA and GHSA were allowed to run for 50,000 iterations with these common parameters: $HMCR = 0.95, HMS = 10$.

Method\Results	Fuel cost ($/h)	Time (s)
Mathpower	130 005.080	600.000
HSA	129 643.652	15.766
IHSA	129 626.923	13.657
GHSA	129 766.680	4.766
FHSA	129 620.166	1.090

Table 9. Comparison of FHSA with other methods

Figure 26 plot total fuel cost with respect of function evaluations. We can say that the proposed algorithm is performing well in the solution of Economic Dispatch problem regarding the difference between the results of the FHSA and the other methods. Even if HSA, IHSA, GHSA are performing well in fuel cost and computing time compared to Matpower method, FHSA is doing better.

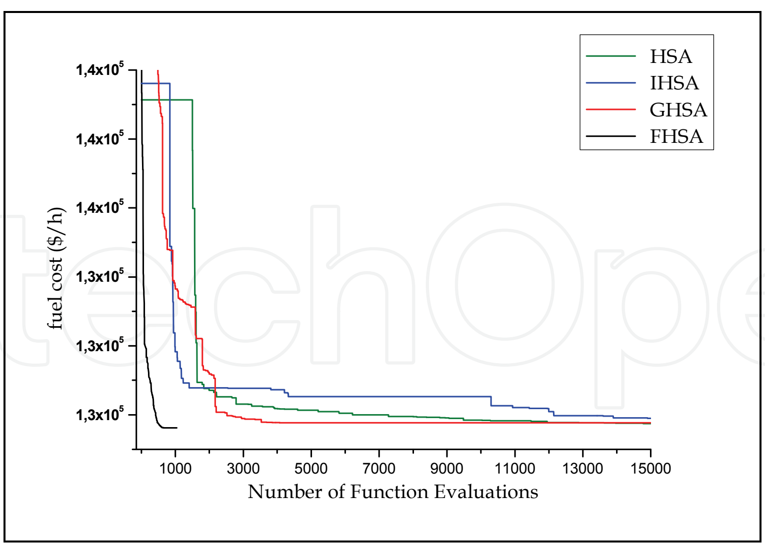

Fig. 26. Fuel cost

5. Conclusion

In this paper, a new Fast and efficient method based on Harmony Search Algorithm (FHSA) for optimizing unimodal functions is proposed. The performance of FHSA is investigated

and compared with HSA, IHSA and GHSA for the optimization of De Jong's function and Rotated hyper-ellipsoid function. Numerical results reveal that the optimization process of HSA, IHSA and GHSA is influenced by the increase of the space dimension and the search space. Thanks to space search reduction, FHSA can find optimum solutions with reduced number of function evaluations. Moreover, the optimization process of FHSA is less sensitive to the diminution of HMCR. Satisfactory results are obtained by adapting FHSA to Economic Dispatch problem and found that the results are better than those obtained by the previous versions of HSA and Matpower.
The stability of the FHSA to the increase of the space dimension and the search space compensates its disadvantage of being applicable only to unimodal functions as is the case of many optimization problems.

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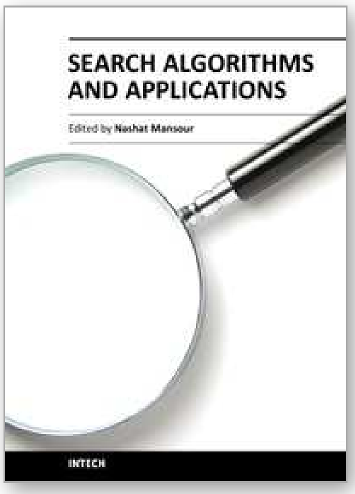

Search Algorithms and Applications
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Search algorithms aim to find solutions or objects with specified properties and constraints in a large solution search space or among a collection of objects. A solution can be a set of value assignments to variables that will satisfy the constraints or a sub-structure of a given discrete structure. In addition, there are search algorithms, mostly probabilistic, that are designed for the prospective quantum computer. This book demonstrates the wide applicability of search algorithms for the purpose of developing useful and practical solutions to problems that arise in a variety of problem domains. Although it is targeted to a wide group of readers: researchers, graduate students, and practitioners, it does not offer an exhaustive coverage of search algorithms and applications. The chapters are organized into three parts: Population-based and quantum search algorithms, Search algorithms for image and video processing, and Search algorithms for engineering applications.